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***Abstract*— This paper proposes a hierarchical control scheme which applies optimization method into DC microgrids in order to improve the system overall efficiency while considering the State-of-Charge (SoC) balancing at the same time. Primary droop controller, secondary voltage restoration controller and tertiary optimization tool formulate the complete hierarchical control system. Virtual resistances are taken as the decision variables for achieving the objective. simulation results are presented to verify the proposed approach.**

Keywords—hierarchical control; state-of-charge; efficiency; genetic algorithm; consensus algorithm

I. Introduction

In a small scale DC microgrid (MG) [1] system with renewable energy systems (RES) and energy storage systems (ESS), as shown in Fig. 1, power converters are installed as interfacing equipment between energy resources and the common bus (CB). RES units can operate on maximum power point tracking (MPPT) mode supplying power to the CB. Under islanded operation mode, ESS units are required to provide voltage support to the CB. Basically, droop control is adopted in primary level for voltage regulation and power sharing among ESSs. Secondary control can be employed to restore the voltage deviation caused by droop control.

Considering the fact that, in this kind of small scale system, the power losses are mainly caused by the power converters. Considering the typical efficiency curve of power converters, there exists an enhancement room for improving the overall efficiency of droop controlled paralleled DC/DC converters especially under light load conditions. Accordingly, a tertiary optimization method was proposed in [2], [3], which took virtual resistances (VR) as decision variables to operate the converters with optimal sharing proportions.

However, the above mentioned work did not take into account the type of energy resources. If multiple ESS units are installed in the system (such as the case shown in Fig.1), state-of-charge (SoC) balancing becomes a critical issue, since imbalanced using of ESSs may cause over dis-/charge of some units, resulting in reduced lifetime and unscheduled ESS

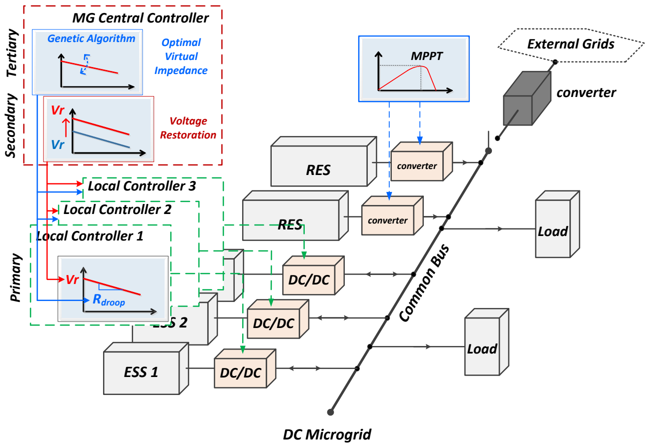

Fig. 1. Study case DC microgrid system.

offline. To solve this issue, a number of methods have been reported, such as secondary SoC coordinated control [4], adaptive droop control [5], fuzzy logic SoC scheduling [6], voltage scheduling for SoC balancing [7], and so on [8], [9]. Although autonomous SoC regulation is realized with above mentioned methods, system efficiency objective has never been integrated.

In order to achieve both SoC balancing and efficiency enhancement, this paper proposes a formulation of optimization problem which properly integrates power loss and SoC difference into one objective function. Genetic algorithm is implemented in tertiary level for searching for near optimum. VRs are used as decision variables to adjust the current sharing proportion. Droop control as well as inner voltage and current control loops are implemented in ESS local controllers (LC), voltage restoration control and VR values optimization functions are implemented in a MG central controller (MGCC) formulating the complete hierarchical control structure.

This paper is organized as follows. Section II introduces the control objectives and formulates the optimization problem. Section III proposes the distributed hierarchical control scheme based on consensus algorithm. To validate the proposed method, Section IV gives the simulation results. Section V makes the conclusion.

II. Control Objective and Optimization Problem Formulation

A. *Efficiency Analysis of Paralleled Converters*

The typical efficiency curve of DC/DC converters [10] and the basic principle of VR shifting are shown in Fig. 2. Assuming the stable input and output voltage, the efficiency of each converter is changing with their output current. The maximum efficiency is usually obtained between 1/3 load to full load conditions. Accordingly, it is not efficient that all the converters equally share the load current as opposed to the conventional static droop control especially under light load conditions.

As droop control is implemented in each local controller, it is possible to change their VRs so as to adjust the load current sharing proportion among all the converters. The general method is outlined in Fig. 2, in which a two-converter system is analyzed. They are given the same voltage reference (V_{ref}). If fixed VRs are applied, the two converters are equally supplying the total load current (i_{o1}=i_{o2}=I_{load}/2). In light load conditions as shown in the figure, it was demonstrated in [3] that the system overall efficiency can be enhanced if the sharing proportion among converters is differentiated.

The objective of the system efficiency enhancement is to minimize the system total power losses. The power conversion loss (P_L) of each converter can be defined as:

$$P_{Lm} = V_{DC} \cdot i_{om} \cdot \frac{1-\eta_m}{\eta_m} \tag{1}$$

where V_{DC} is DC bus voltage, i_{om} and η_m are the output current and efficiency of the m^{th} converter, which can be calculated as:

$$\eta(i_o) = 0.975 \cdot e^{-2\times 10^{-3} \cdot i_o} - 0.1257 \cdot e^{-0.3 \cdot i_o} \tag{2}$$

B. *Practical Consideration on SoC balancing*

The essence of the system power losses minimization is to differentiate the power output of ESSs under different load conditions. However, the differentiation may result in imbalanced dis-/charging of ESS units causing over charge or discharge of them. Accordingly, the *depth-of-discharge* (*DoD*) needs to be also considered in the optimization problem.

C. *Optimization Problem Formulation*

Considering the importance of both efficiency enhancement and SoC balancing, they can be combined into the objective function defined as:

$$f_{obj} = \sum_{m=1}^{N} DoD_m \cdot P_{Lm} \tag{3}$$

where DoD_m is the *depth-of-discharge* of the m^{th} ESS, N is the total number of operating units. The essence of this definition

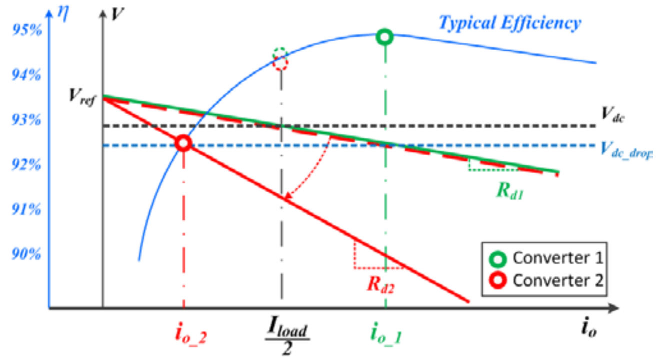

Fig. 2. Typical efficiency curve and adaptive VRs.

is that units with higher DoD value are considered consuming higher power losses during the optimization procedure and the output current of which will be reduced. This simple but effective strategy can finally balance the SoC level while also improve system overall efficiency.

The VR values in each local control system are selected as the decision variables. The load current sharing proportion can be adjusted by changing VR values:

$$i_{o1} : i_{o2} : \ldots : i_{oN} = \frac{1}{R_{d1}} : \frac{1}{R_{d2}} : \ldots : \frac{1}{R_{dN}} \tag{4}$$

The advantage of using VRs as decision variables is that by changing VR values, the load current sharing proportion among all the converters can be proportionally adjusted, while the total current generated and supplied are always balanced. However, the common bus voltage and the system level stability are certainly affected. Distributed secondary control restores the DC bus voltage, and detailed analysis of stable VR range are presented in [3].

This optimization problem is subjected to:

$$s.t.: \begin{cases} 0.25 \le \left\{ R_{d1}, R_{d2}, \ldots, R_{dN_{oC}} \right\} \le 5 \\ \left\{ i_{o1}, i_{o2}, \ldots, i_{oN_{oC}} \right\} \le I_{MAX} \end{cases} \tag{5}$$

which states that the shifting range of VRs should be within a certain stable range and the output current of each converter is limited to I_{MAX}. Considering the non-convex feature of the objective function, genetic algorithm (GA) is used in this paper to solve this optimization problem.

D. *Performance Evaluation of GA*

In order to solve the optimization model formulated above, a proper algorithm should be implemented. The selection of algorithms is based on the analysis of objective function. Global and local optimization methods are taken into option. The fastest optimization algorithms only seek local optimum

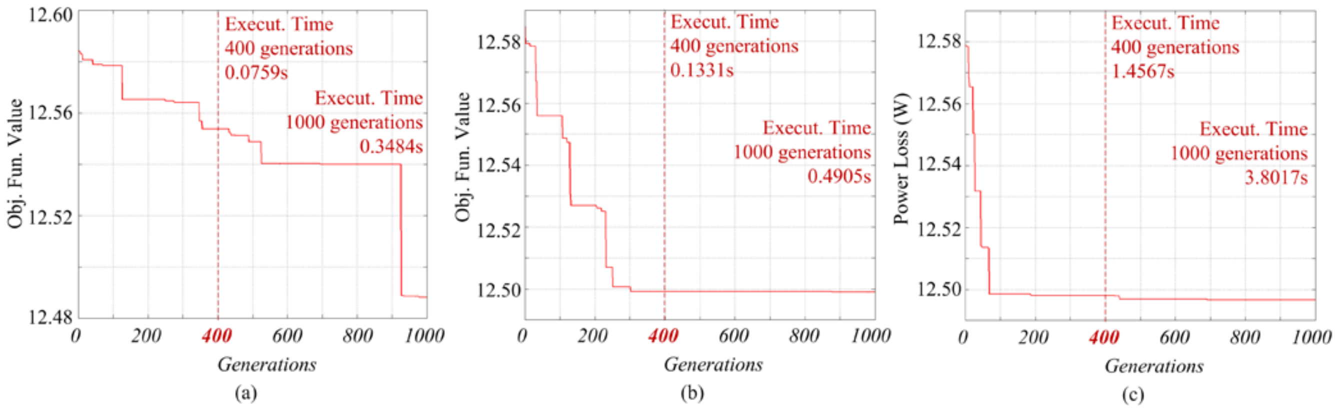

Fig. 3. Optimization algorithm performance evaluation: (a) N_{pop}=10; (b) N_{pop}=100; (c) N_{pop}=1000.

point which is called local optimization, such as simplex method and gradient based algorithms. However, local optimization does not guarantee global optimal solution. On the other hand, global optimization algorithms, such as genetic algorithm (GA) and Particle Swarm Optimization (PSO), are able to find global optimum. However, they may require more computational time and memory space. Consequently, preliminary analysis and tests are necessary for selecting a proper algorithm and improving its performance.

The basic parameters of GA significantly influence the performance of the program [11], [12]. For different sorts of problems, good parameter settings of GA can be significantly different. Parameter tuning and tests are necessary for ensuring that the algorithm gives reliable and optimal solutions.

When selecting parameters, such as population size (N_{pop}) and maximum number of generations (N_g), there is usually a tradeoff between computational time and quality of final solutions. In addition, as these parameters cannot be treated separately, a rational matching is also important.

In order to test the performance of the optimization algorithm, the objective function value in each generation is plotted in Fig. 15 (in a 3-ESS system). The population size in each case is set to (a) N_{pop}=10, (b) 100 and (c) 1000 respectively. In Fig. 3 (a), with small population number, the time for finishing 400 and 1000 generations is shorter compared with the other two cases, however, the optimality of the final solution cannot be guaranteed within 1000 generations. In Fig. 3 (b), population size is set to 100, algorithm can find near optimal solution within 400 generations (0.1331s). Similarly, in Fig. 3 (c) with population size of 1000, the algorithm can find near optimal solution within 100 generations. However, with larger population size, the memory size and the consumption time are largely increased resulting in higher computational cost. Reasonable selection is to choose the parameters in Fig. 3 (b) (N_{pop}=100), the program can find near optimal solution within 400 generations consuming less than 0.2s.

Based on the above problem formulation and program selection, optimization algorithm can be implemented in the top level of hierarchical control scheme to achieve better system operation.

III. PROPOSED HIERARCHICAL CONTROL SCHEME

Hierarchical control was proposed for handling different control objectives under different time scales. Primary control includes inner voltage/current control loops and power sharing control loops (i.e. droop control and virtual impedance); Secondary control can be dedicated to power quality regulation; Optimization and energy management functions are usually implemented in tertiary level for optimizing the overall system performance. Generally, each higher control level needs to be approximately an order of magnitude slower than the down streaming level [1], [13] so as to decouple the behavior of different levels.

Based on the hierarchical control concept, the proposed control scheme is shown in Fig. 4. Droop controlled DC-DC converter acts as a voltage source in series with VR (R_d). In primary control, droop control method is implemented which includes the VR control loop expressed as:

$$v_{dc} = v_{ref} - R_d \cdot i_o \tag{6}$$

where i_o is the output current of each unit, R_d is the VR value, and v_{ref} is the output voltage reference at no load. Usually VR is fixed by the maximum allowed voltage deviation and maximum output current.

Primary loop ensures power sharing and stable operation, however, according to (6), the voltage deviation is inherent and depends on load current. In order to solve this problem, voltage secondary control is implemented. The dc bus voltage is sensed and compared with desired voltage V_{ref}^*, with the voltage error being sent to a PI (Proportional-Integral) controller to generate a compensating quantity δv for each converter reference:

$$\delta v = k_p (V_{ref}^* - v_{dc}) + k_i \int (V_{ref}^* - v_{dc}) dt \tag{7}$$

Then the reference voltage with secondary voltage restoration can be generated as:

$$v_{ref} = V_{ref}^{*} + \delta v \tag{8}$$

Finally, tertiary level receives system data including the number of operating converters, the rated power and output current of each converter. Received information is processed

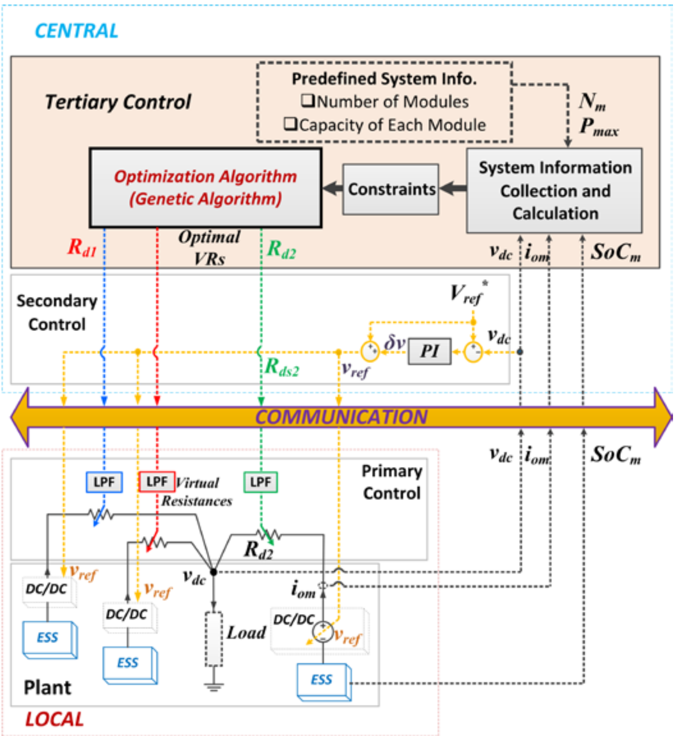

Fig. 4. Hierarchical Control Scheme.

by optimization algorithm to find the optimal load current sharing proportion. VRs are the actual decision variables for adjusting sharing efforts of each converter. However, in order to keep stable operation while changing VRs, similar sensitivity study and stability analysis can be conducted as was done in [2], [3]. Also, a 1st order butterworth low pass filter (LPF) is required between higher level regulation and primary droop to smooth the shifting of VRs, so as to decouple the dynamics of different control levels. Generally, each higher control level needs to be approximately an order of magnitude slower than the down streaming level [1], [13].

IV. Simulation Results

In order to test the performance of the proposed control scheme, simulation has been conducted in Matlab/Simulink environment. An islanded DC microgrid system is used as the study case. Three ESS units and several other sorts of energy resources (RES, diesel generator, etc.) are implemented. Buck converters are used between ESS and the common bus as an example. The RES generation follows MPPT scheme, while the ESS units are controlled based on the proposed method in order to providing voltage support to the islanded system while also take care of energy balancing. The capacities of the three ESS units are assumed to be the same. A load profile is input to the system to evaluate the system response.

Three cases are simulated: a) Case 1, non-optimized system, see Fig. 5; b) Case 2, efficiency optimized system, see Fig. 6; c) Case 3, efficiency optimized with SoC balancing system, see Fig. 7. Efficiency and conversion losses of the three cases are compared in Fig. 8. Detailed analysis of the results is given in the following parts.

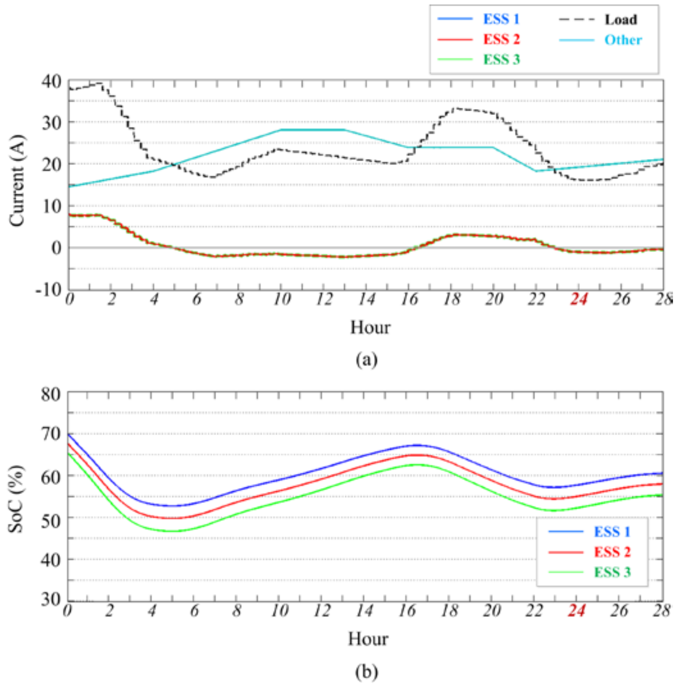

Fig. 5. Case 1, non-optimized system: (a) SoC of ESS units; (b) system current flow.

A. Case 1: Non-optimized System

A random load current profile is input to the system as shown in Fig. 5 (a) (dashed black curve). Current generation from other resources covers most of the energy consumption, and the ESS units compensate the energy imbalance within the system. In non-optimized system, the currents of the three ESS units are always proportionally shared according to their power ratings and capacities. Accordingly, their currents are equally shared in this case as shown in Fig. 5 (a) (overlapped curves), also the SoC levels are equally changed as shown in Fig. 5 (b).

Although the power between generation side and consumption side is well balanced because of using of ESS units, the optimality of the system efficiency is not guaranteed. Comparison is made in the following part with other cases.

B. Case 2: Efficiency Optimized System

As was proposed in [2], [3], in order to improve the system efficiency (especially reducing the power conversion losses), the sharing proportion among converters should be differentiated according to different total currents. Based on this strategy, simulation is conducted with results shown in Fig. 6. The efficiency optimization tends to employ the units with higher efficiency (ESS 1 is assumed to have higher efficiency) under light load conditions which may result in over use of them as shown in Fig. 6. As ESS1 is assumed the higher efficiency units, it is always used under different load conditions (see blue curve in Fig. 6 (a)). It also can be seen in Fig. 6 (b) that the SoC level of ESS1 is changed significantly during the hours. Finally, the SoC levels of the ESS units are largely differed.

Although this strategy can offer enhanced system efficiency compared with non-optimized case (see Fig. 8 (a) comparison between case 1 and case 2), the SoC balancing issue is omitted which may cause over dis-/charging of some ESS units and reduce their lifetimes.

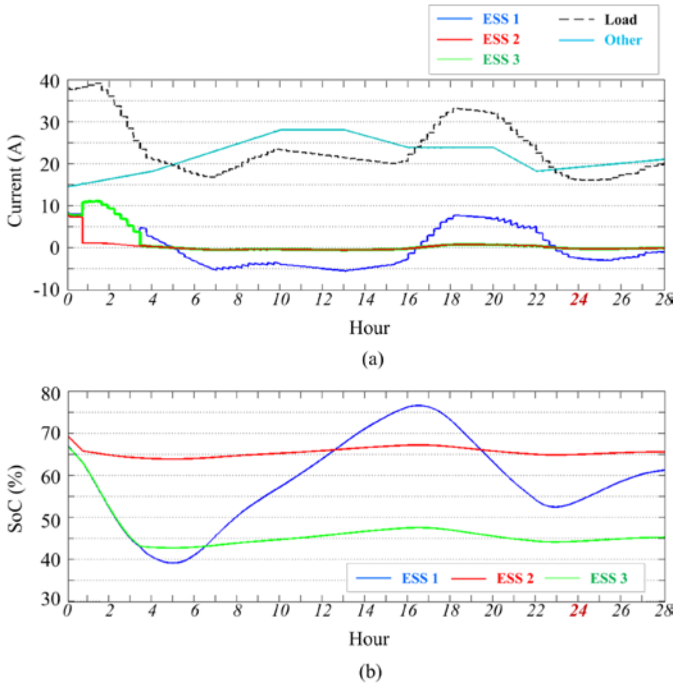

Fig. 6. Case 2, efficiency optimized system: (a) SoC of ESS units; (b) system current flow.

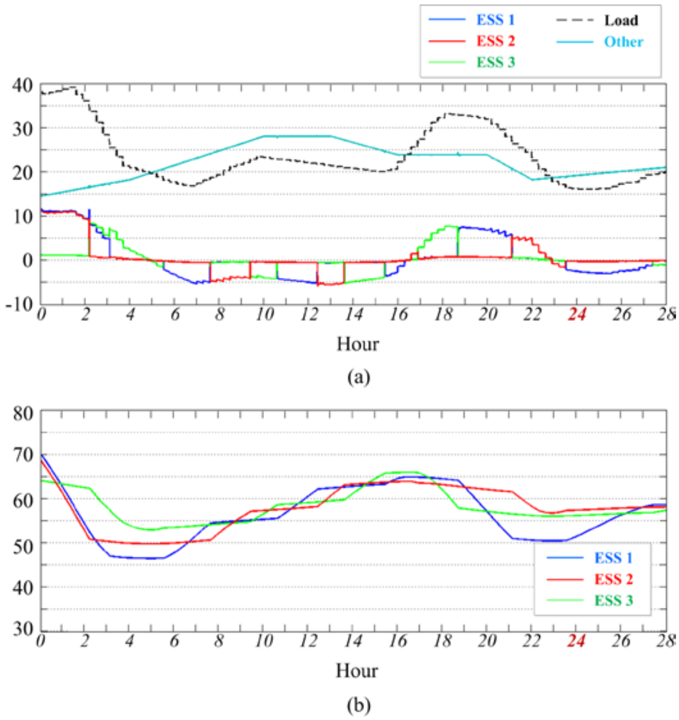

Fig. 7. Case 3, efficiency optimized with SoC balancing system: (a) SoC of ESS units; (b) system current flow.

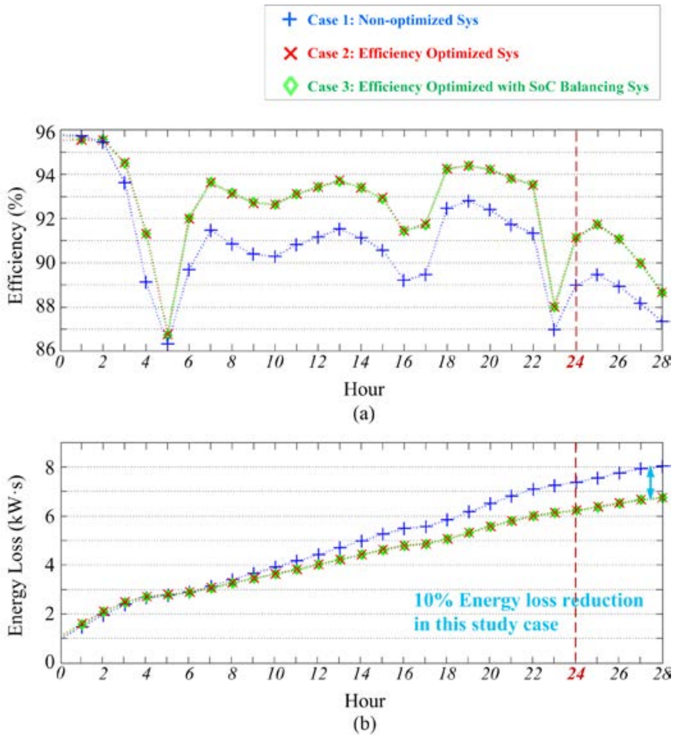

Fig. 8. System efficiency and energy losses comparison.

C. *Case 3: Efficiency Optimized with SoC Balancing System*

To balance the SoC level while also improve the overall system efficiency, the proposed method is implemented with the simulation results given in Fig. 7. It can be seen from the current curves of the ESS units that they are alternately used according to the SoC level and efficiency optimization results. The differences of the SoC levels between the three ESS units are always kept within 10% during the operation process. As one of the advantages of the proposed method, the operation of the ESS units is automatically scheduled according to their SoC levels.

The efficiency comparison is shown in Fig. 8 (a) case 3, which shows that the proposed method offers enhanced system overall efficiency compared with case 1 non-optimized system while also keeps well balanced SoC level compared with case 2. The total energy conversion losses are compared in Fig. 8 (b) showing that in this study case 10% energy loss can be reduced by applying efficiency optimization.

V. CONCLUSION

This paper proposes a hierarchical control scheme aiming to integrate SoC balancing objective into the system efficiency optimization problem. A study case islanded DC microgrid is used including three ESS units and some other sorts of energy resources. System efficiency and SoC balancing issue are analyzed. Optimization problem is formulated according to the consideration of both objectives. Genetic algorithm is selected and evaluated with the study case problem. Simulation results are given to show the strategy and performance of the proposed control scheme. Comparisons are made between three study cases which demonstrate that the proposed method realizes both efficiency enhancement and SoC balancing objectives.

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